Persistent Monetary Non-neutrality in an Estimated Model with Menu Costs and Partially Costly Information*

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September 29, 2016

*The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Central Bank of Brazil.

Motivation

- "Micro-macro disconnect"
  - Many large, frequent price changes
  - Aggregate evidence of large degree of monetary non-neutrality
- Models: Different pricing frictions $\longrightarrow$ different micro and macro implications
  - menu costs $\longrightarrow$ state-dependent rules that fit microdata reasonably well, but small non-neutrality (e.g. Almeida and Bonomo 2002, Golosov Lucas 2007)
  - information frictions $\longrightarrow$ larger real effects of monetary shocks, but nominal price adjustments typically occur continuously (e.g. Reis 2006, Maćkowiak and Wiederholt 2009)
- Type of pricing friction and frequency of price adjustments $\longrightarrow$ difficulties in matching micro and macro evidence

What we do

- Propose new model of price-setting that reconciles:
  - micro evidence of nominal rigidity and relatively frequent price adjustments
  - macro evidence of persistent real effects of monetary shocks
- Methodology to solve the model
- Estimation by SMM using price-setting statistics derived from micro data for U.S. (courtesy of Oleksiy Kryvtsov)
- Efects of monetary shocks in estimated model

What we do

- Model features
  - time- and state-dependent pricing:
    - costs of changing prices (K)
    - partial information freely available
    - remaining information entails lump-sum cost (F)

What we do

- When idiosyncratic information is free and aggregate information is costly (corroborated by estimation), the model:
  - matches U.S. price-setting statistics
  - produces persistent macroeconomic effects

- Mechanism: free information about idiosyncratic shocks $\longrightarrow$ frequent price adjustments and low frequency of aggregate information collection $\longrightarrow$ persistent effects of aggregate shocks.
  - Reminiscent flavor of, e.g., Maćkowiak and Wiederholt (2009)
  - Estimated model matches price-setting statistics from micro data

Some related work

- On optimal rules with information and adjustment costs:
  - Bonomo and Garcia (2002), Bonomo and Carvalho (2004, 2010), Gorodnichenko (2010), Abel, Eberly, and Panageas (2010), Alvarez, Guiso, and Lippi (2012), Alvarez, Lippi and Paciello (2011)
- On the mechanism: frequent updating wrt idiosyncratic shocks and infrequent updating wrt aggregate shocks:
  - Maćkowiak and Wiederholt (2009), Klenow and Willis (2007), Knotek (2009).

Outline

Partial information model

Costly information only

Estimation

Monetary non-neutrality

Partial information model

- p_t^*: frictionless optimal price (full information; no menu cost)

- Adjustment cost K, information cost F
  - a firm always has the option to pay K to adjust its price
  - a firm always has the option to pay F to have full information

- Firms' objective: minimize PDV of expected total costs
  - integral of flow profit losses: $\propto (p_t - p_t^*)^2$
  - adjustment costs K and information costs F

Partial information model

- Firm forms probabilistic assessment of $E_t(p_t - p_t^*)^2$

- We decompose:

$$\begin{aligned} E_t(p_t - p_t^*)^2 &= (p_t - E_t p_t^*)^2 + E_t(p_t^* - E_t p_t^*)^2 \\ &= (p_t - E_t p_t^*)^2 + Var_t\,(p_t^*)\,, \end{aligned}$$

- $(p_t - E_t p_t^*)^2 =$ flow cost of deviating from the *expected* level of the frictionless optimal price

- $E_t(p_t^* - E_t p_t^*)^2 = Var_t(p_t^*) =$ expected flow cost from not continuously entertaining information about p_t^*

Partial information model

- $dp_{it}^{*} = \mu dt - \sigma_f dW_{ft} - \sigma_c dW_{ct}$, where W_{ft} and W_{ct} are independent standard Wiener processes

- Information about W_{ft} is continuously and freely available, costless to process

- Full information about W_{ct} entails lump-sum cost F

- Define *time elapsed since the last information date*:

$$\tau = t - t_0$$

- And *expected price discrepancy*:

$$z_t = p_t - E_t p_t^{*}$$

Partial information model

- Thus:

$$\begin{aligned} E_t(p_t - p_t^*)^2 &= z_t^2 + Var_t(p_t^*) \\ &= z_t^2 + \sigma_c^2 \tau \end{aligned}$$

- In the inaction (no adjustment or info. collection) range z_t and τ will evolve as:

$$dz_t = -\mu dt + \sigma_f dW_{ft}$$

and

$$d\tau = dt$$

Partial information model

- $V(z_t, \tau)$: optimized value of the firm's dynamic cost-minimization problem

- Bellman equation in the (adjustment/information) inaction region:

$$V(z_t, \tau) = \left(z_t^2 + \sigma_c^2 \tau\right) dt + e^{-\rho dt} E_t V(z_{t+dt}, \tau + dt) \tag{1}$$

- The differential form of the Bellman equation (1) is written as (Ito's lemma):

$$\frac{1}{2}\sigma_f^2 V_{zz}(z, \tau) - V_z(z, \tau)\mu + V_\tau(z, \tau) - \rho V(z, \tau) + z^2 + \sigma_c^2 \tau = 0.$$

Partial information model - the adjustment decision

- Adjustment inaction region $\{l(\tau), c(\tau), u(\tau)\}$

- Lump-sum adjustment costs:

$$c(\tau) = \arg\min_z V(z, \tau)$$

- Adjustment always an option:

$$V(z, \tau) \leq V(c(\tau), \tau) + K$$

- Boundaries of inaction region satisfy:

$$V(l(\tau), \tau) = V(c(\tau), \tau) + K$$
$$V(u(\tau), \tau) = V(c(\tau), \tau) + K$$

Partial information model - the information decision

- Information policy $\tau^*(z)$

- When information is collected at time τ, history of W_{ct} is revealed:
  - Expected discrepancy z_t receives a shock with distribution $N(0, \sigma_c^2 \tau)$
  - Time elapsed τ is reset to zero
  - $V(z, \tau)$ becomes $V(z + \sigma_c \sqrt{\tau} \varepsilon, 0)$, which is uncertain before information collection.

Partial information model - the information decision

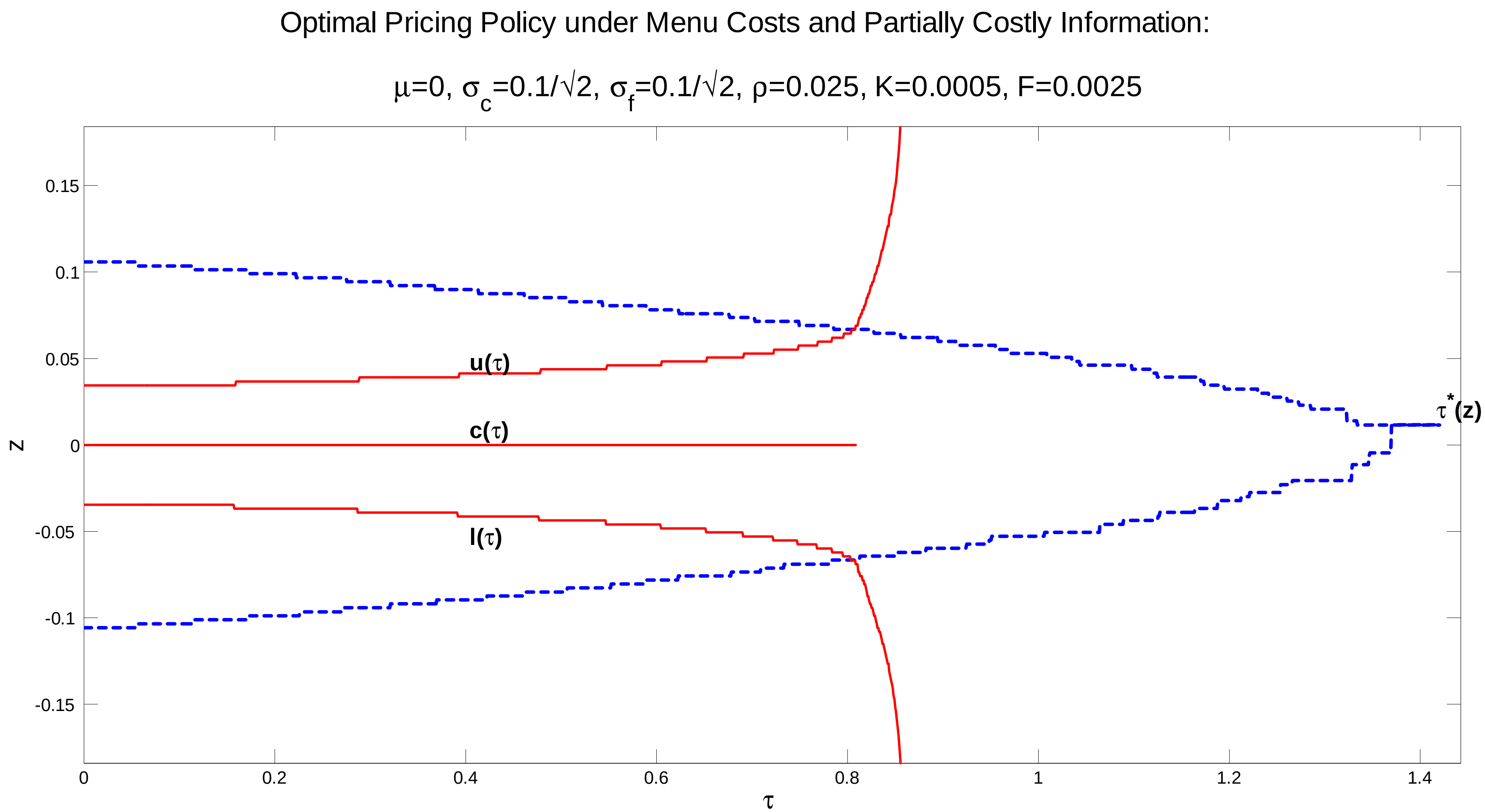
- Since paying F and collecting/processing information is always an option, it must be true that

$$\forall (z,\tau), \quad V(z,\tau) \leq E\left[V\left(z+\sigma_C\sqrt{\tau}\varepsilon, 0\right)\right] + F$$

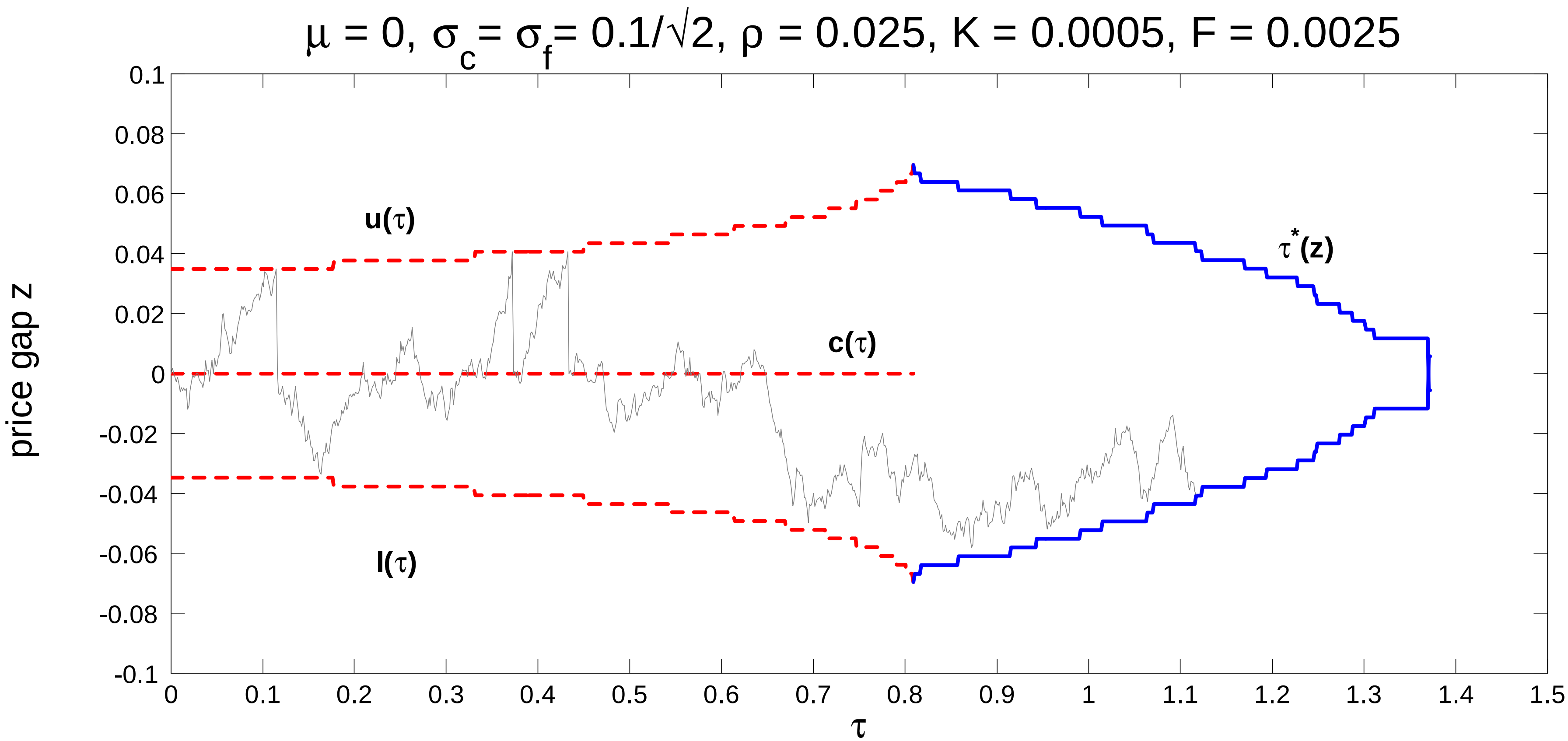
- The boundaries of the information inaction region satisfy:

$$V(z,\tau^*(z)) = E\left[V\left(z+\sigma_C\sqrt{\tau^*(z)}\varepsilon, 0\right)\right] + F$$

Partial information model



Partial information model



Costly information only

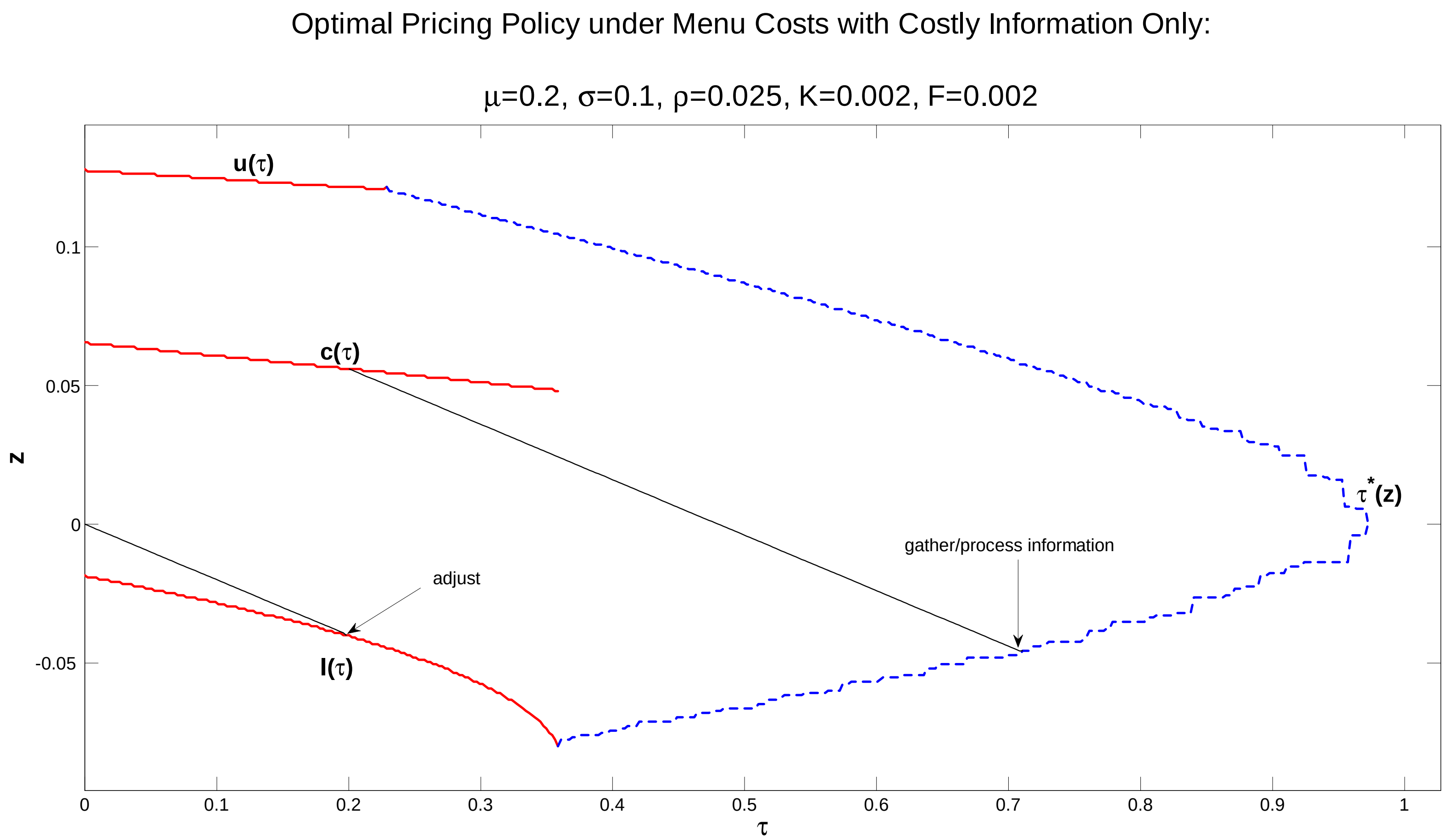
- Case studied by Alvarez, Lippi and Paciello (2011)

- Adjustments only on information ("observation") dates

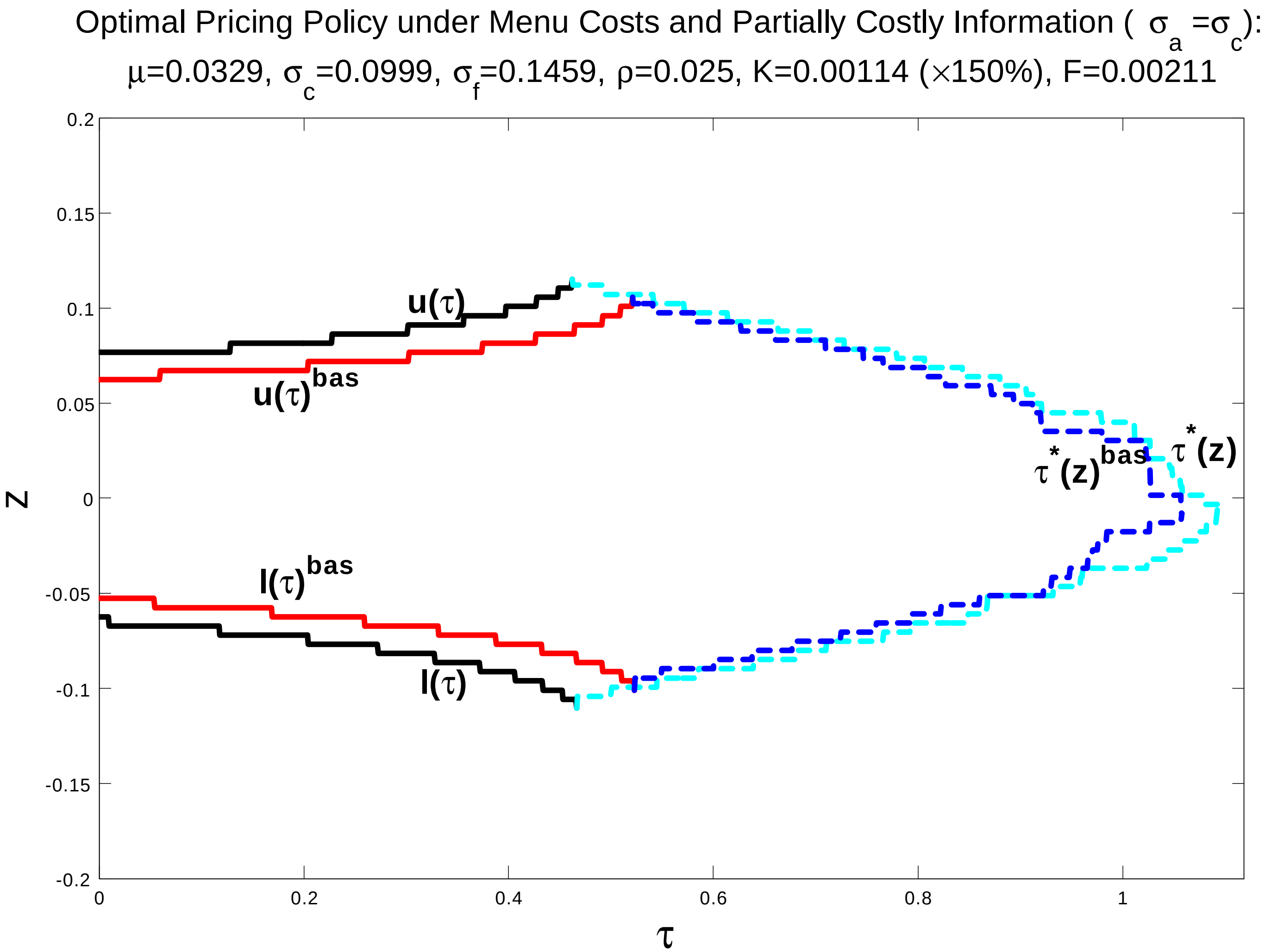
- We allow adjustments without information
  - likely to occur when inflation is high or $K << F$

- Particular case of our model with $W_{ft} \equiv 0$, "$\sigma_c = \sqrt{\sigma_c^2 + \sigma_f^2}$"

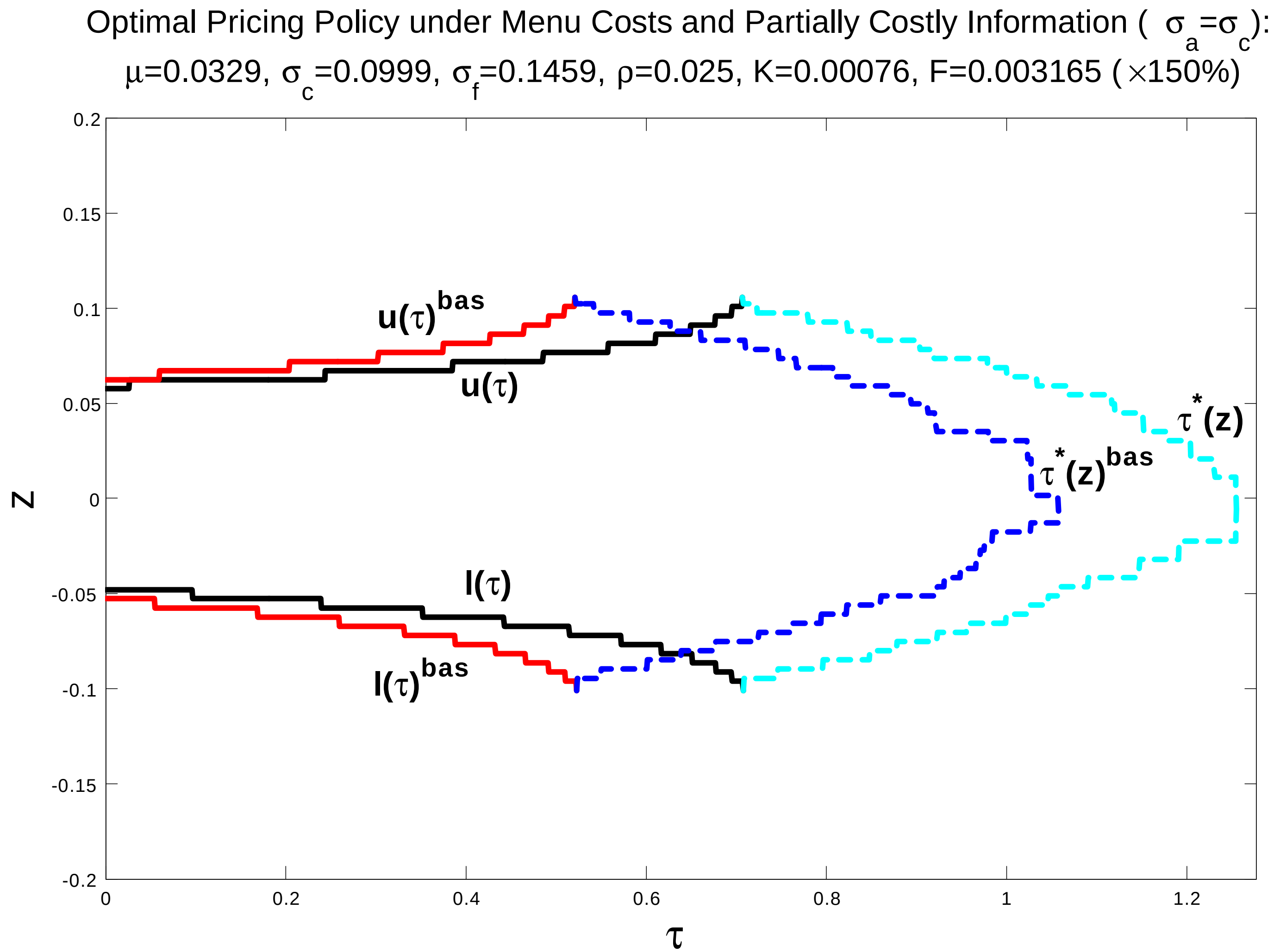
Costly information only



Price setting exercises Increase K



Price setting exercises Increase F



Taking models to the data

- W_{ft}, W_{ct} become W_{at}, W_{it}

- 3 different models

  - idiosyncratic information free, aggregate information costly

  - aggregate information free, idiosyncratic information costly

  - both aggregate and idiosyncratic information costly

Estimation

- Data: monthly price-setting statistics (regular prices) from Klenow-Kryvtsov

- Simulation Methods of Moments (calibrating μ, ρ), estimate σ_a, σ_i, F, K to target $fr\,(\Delta p > 0)\,, fr\,(\Delta p < 0)\,, mean\,|\Delta p|\,, median\,|\Delta p|$, $(fr\,(\Delta p > 0))^2$

- Choice of moments:
  - higher $\sigma_a \longrightarrow$ more variable frequency of adjustments
  - given $\mu > 0$, higher $\sigma_i \longrightarrow$ reduces $(freq\Delta p > 0) - (freq\Delta p < 0)$
  - lower $F \longrightarrow$ increases the proportion of informed adjustments – larger and more variable $\longrightarrow$ changes the relation between the mean and the median of $|\Delta p|$
    - in the case of costly aggregate info. $\longrightarrow$ more variable frequency of adjustments.
  - higher $K \longrightarrow$ reduces both $(freq\Delta p > 0)$ and $(freq\Delta p < 0)$

Estimation

$$\min_{\Phi}\left\{\left(\Psi_{data}-\Psi_{sim}\left(\Phi\right)\right)^{T}W^{*}\left(\Psi_{data}-\Psi_{sim}\left(\Phi\right)\right)\right\}$$

where

$$\Phi=\left\{\sigma_a,\sigma_i,F,K\right\}.$$

and

$$\Psi=\left\{\begin{array}{c}\left[\left(fr\ \Delta p>0\right)_t,\left(\ fr\ \Delta p<0\right)_t\right]_{t=1}^{T},\\ \left[\left(mean\left|\Delta p\right|\right)_t,\left(median\left|\Delta p\right|\right)_t\right]_{t=1}^{T},\\ \left[\left(fr\ \Delta p>0\right)_t^2\right]_{t=1}^{T}\end{array}\right\}$$

Estimation results

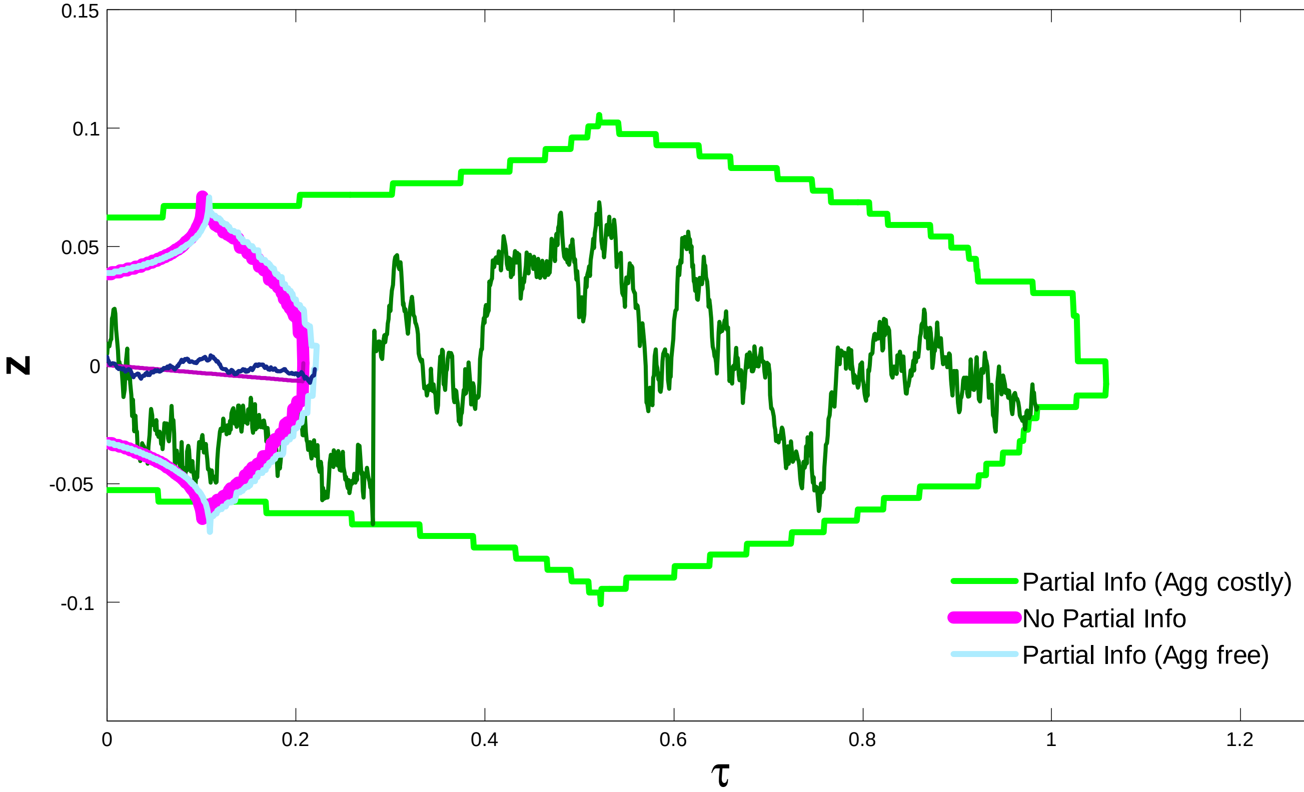
Estimated Parameters				
	$\boldsymbol{\sigma}_a$	σ_i	F	K
No Partial Info	**0.0254**	**0.1905**	**0.00065**	**0.00024**
standard deviation	0.0013	0.0025	1.36e-05	1.03e-05
t-statistic	19.9	74.8	48.0	23.1
Partial Info $(\sigma_a = \sigma_c)$	**0.0999**	**0.1459**	**0.00211**	**0.00076**
standard deviation	0.0004	0.0066	0.0002	0.0002
t-statistic	216.3	22.0	11.6	4.5
Partial Info $\left(\sigma_a = \sigma_f\right)$	**0.0181**	**0.1911**	**0.00071**	**0.00025**
standard deviation	0.0018	0.0033	1.72e-05	6.27e-06
t-statistic	10.1	57.5	41.2	39.6

Estimation results

Target Statistics				
Statistic	$freq\ \Delta p > 0$	$freq \Delta p < 0$	$mean\ \lvert\Delta p\rvert$	$median\ \lvert\Delta p\rvert$
Data	0.1503	0.1152	0.0900	0.0710
No Partial	0.1465	0.1252	0.0953	0.0842
Partial $\sigma_a = \sigma_c$	0.1505	0.1227	0.0915	0.0788
Partial $\sigma_a = \sigma_f$	0.1477	0.1247	0.0949	0.0838

Target Statistics		
Statistic	$(fr\ \Delta p > 0)^2$	$std(freq\ \Delta p > 0)$
Data	0.0233	0.0263
No Partial	0.0221	0.0263
Partial $\sigma_a = \sigma_c$	0.0236	0.0297
Partial $\sigma_a = \sigma_f$	0.0231	0.0356

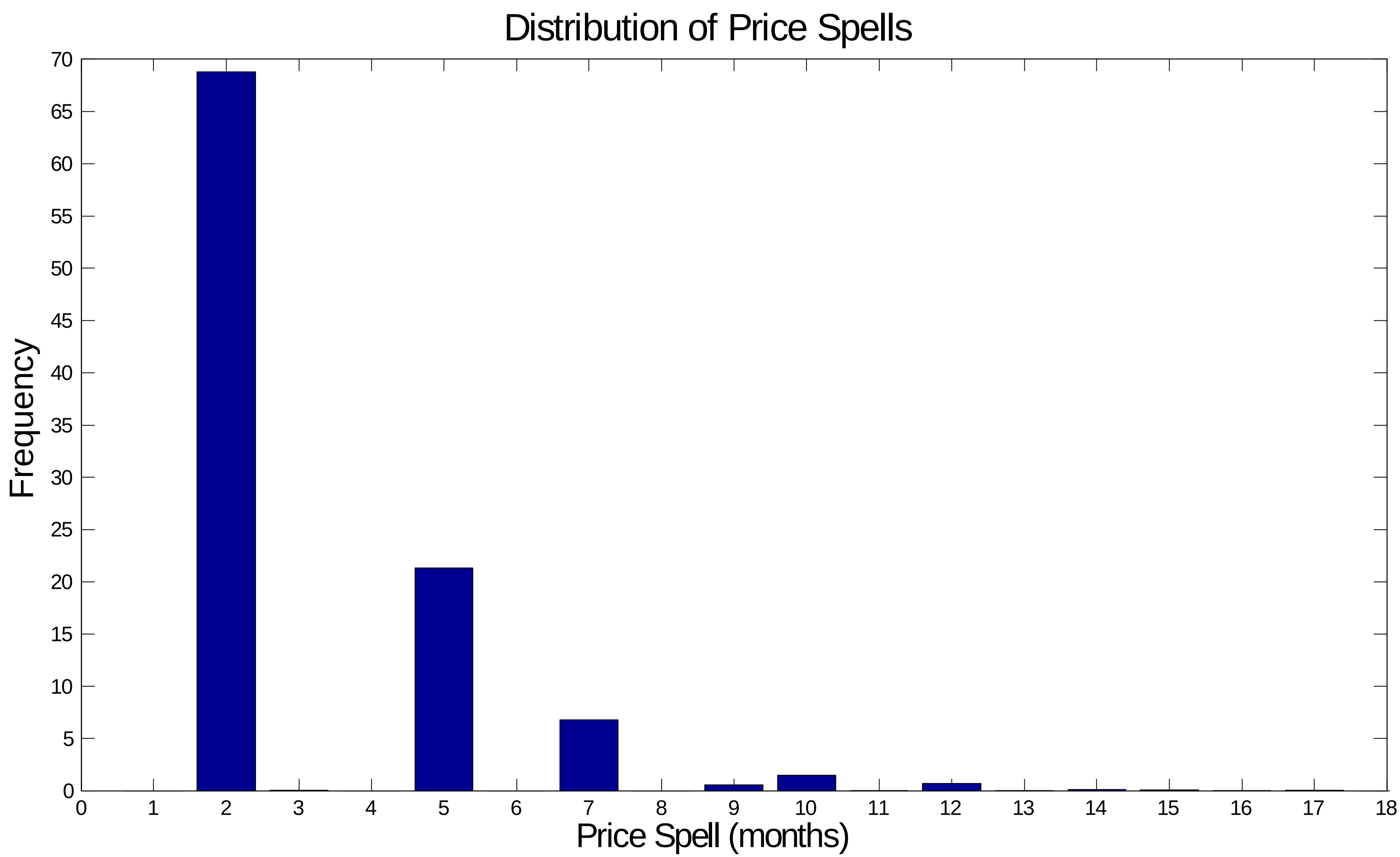
Optimal rules implied by estimation



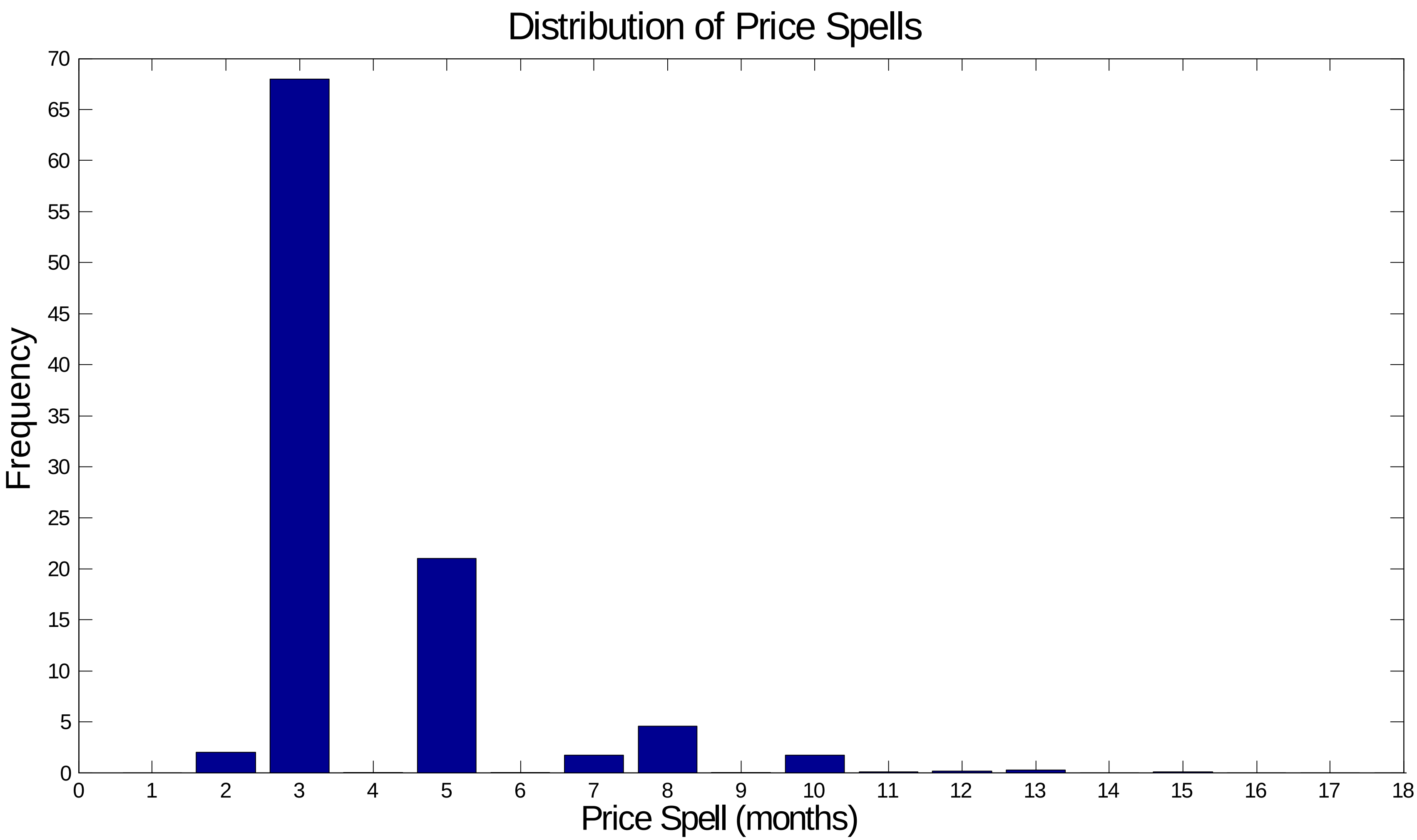
Price setting results

Baseline	No Partial Info	Partial Info $(\sigma_a = \sigma_f)$	Partial Info $(\sigma_a = \sigma_c)$
K	0.00024	0.00025	0.00076
F	0.00065	0.00071	0.00211
Adjustments per year	3.36	3.26	3.59
fully info. adj	100%	98%	25%
adj. without (full) info	0%	2%	75%
Information gatherings per year	4.88	4.64	1.37
resulting in immediate adj.	69%	69%	65%

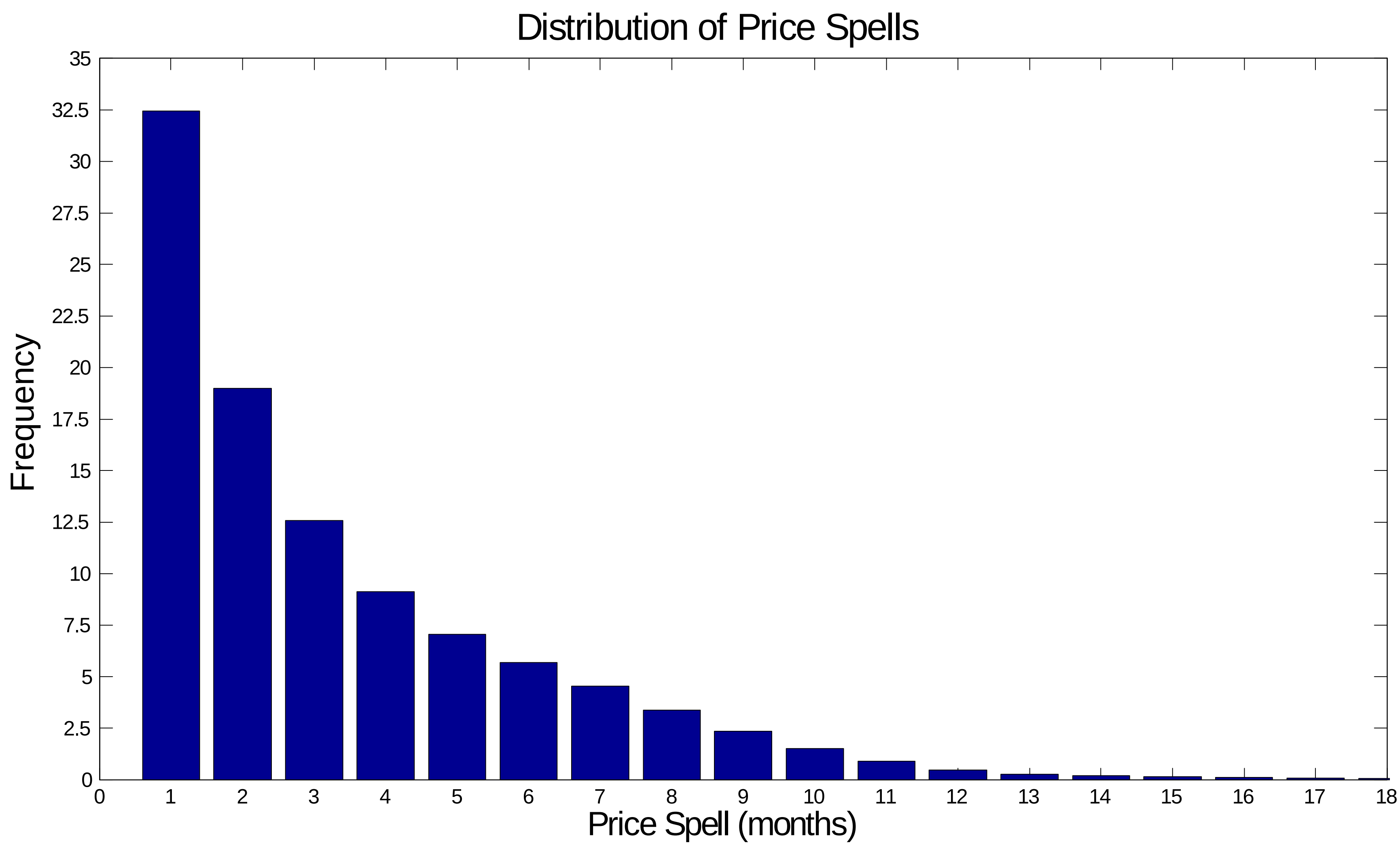
Distribution of Price Spells No Partial Info



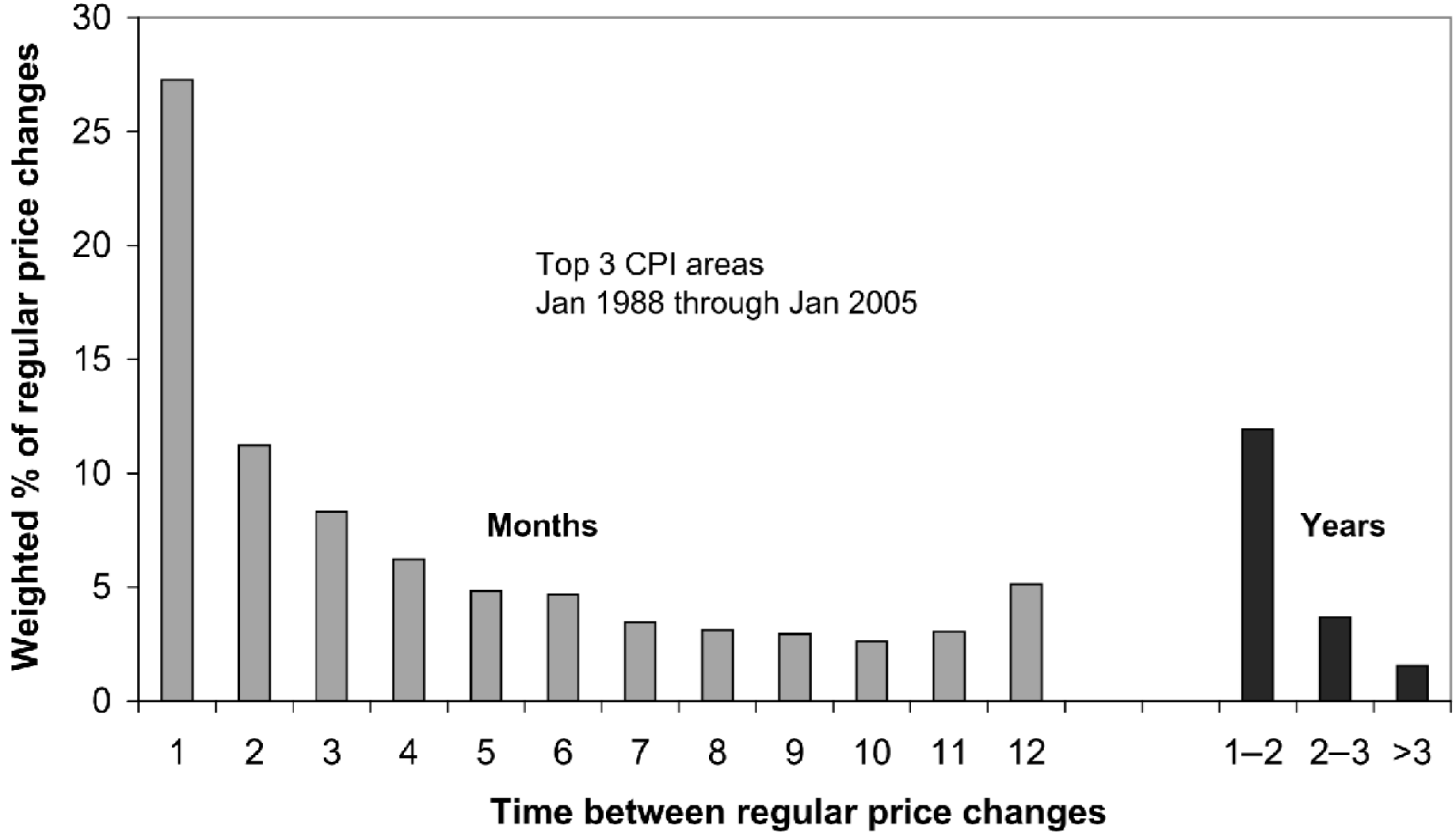
Distribution of Price Spells Partial Info ($\sigma_a = \sigma_f$)



Distribution of Price Spells Partial Info ($\sigma_a = \sigma_c$)



Distribution of Price Spells in Klenow and Kryvtsov



Effect of nominal aggregate demand shock in estimated economies

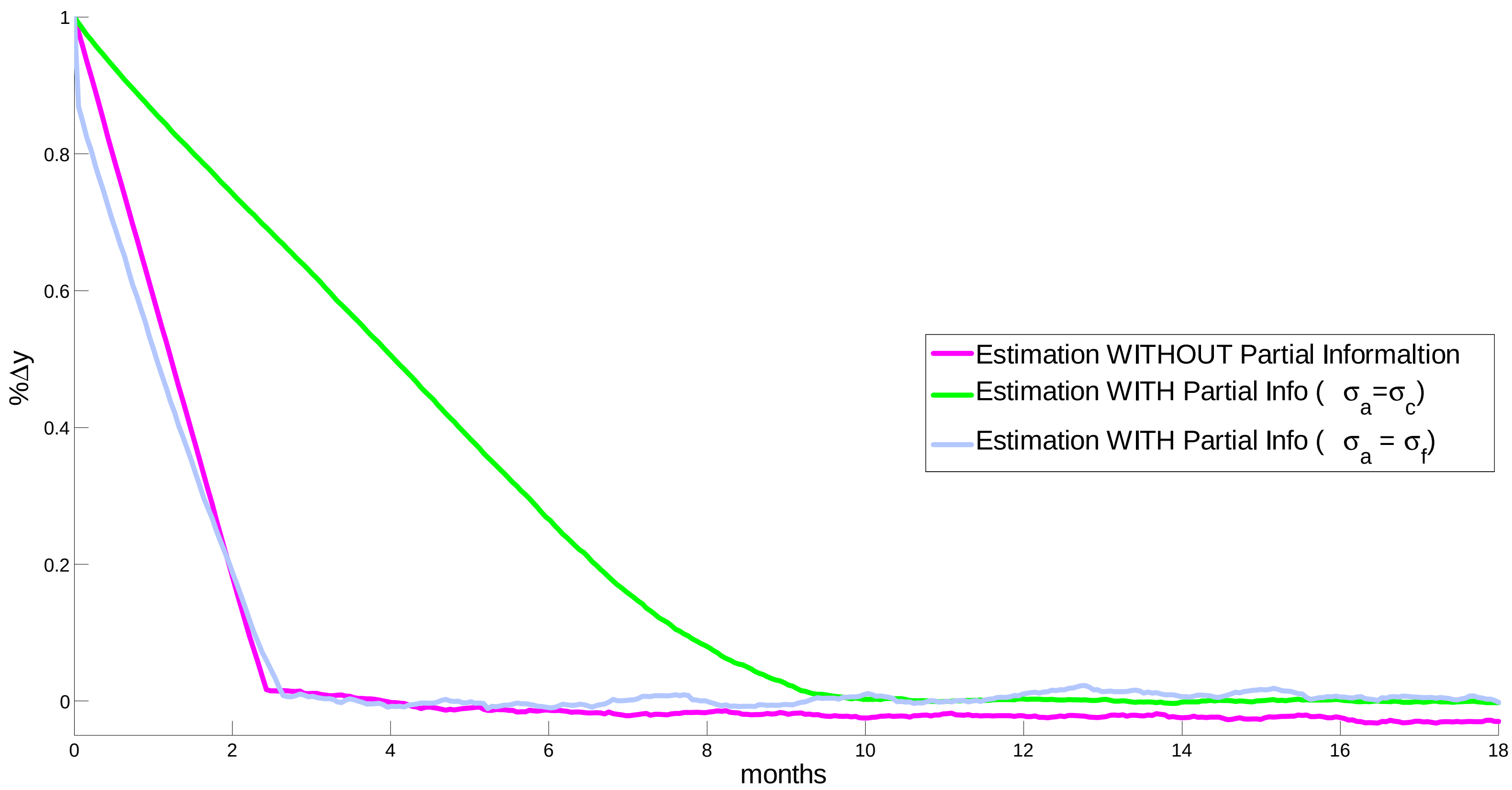
- Level of output is given by:

$$y_t = m_t - p_t$$

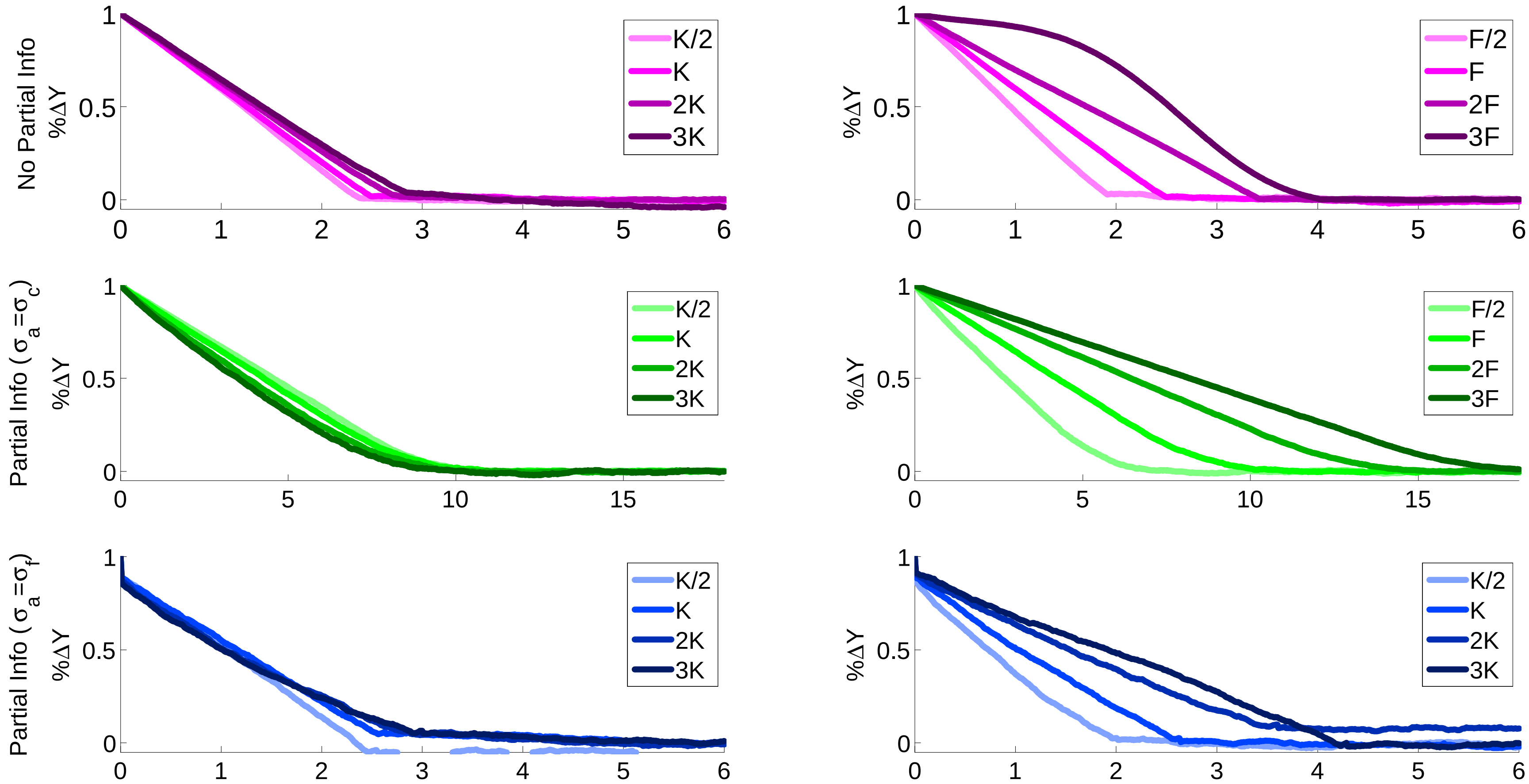
- Nominal aggregate demand m_t grows at rate μ

- After reaching the stochastic steady state:
  - 1% permanent increase in the level of nominal aggregate demand

Effect of nominal aggregate demand shock in estimated economies



Effect of aggregate demand shock: changing K and F



Summing up

- New price setting model with costly price adjustment and partially costly information
  - price adjustments based on partial information
- Estimated partial information model with costly aggregate information:
  - fits price-setting statistics from micro data
  - generates realistic distribution of duration of price spells and
  - much larger monetary non-neutralities
- Helps reconcile empirical micro and macro evidence